

determining FFR for a patient using a trained machine-learning based mapping can be implemented on a computer using well-known computer processors, memory units, storage devices, computer software, and other components. A high-level block diagram of such a computer is illustrated in FIG. 14. The scanner and workstation of FIGS. 7, 8, and 9 can be implemented using the computer of FIG. 14. Computer 1402 contains a processor 1404, which controls the overall operation of the computer 1402 by executing computer program instructions which define such operation. The computer program instructions may be stored in a storage device 1412 (e.g., magnetic disk) and loaded into memory 1410 when execution of the computer program instructions is desired. Thus, the steps of the methods of FIGS. 1, 4, 5, 6, 10, and 12 may be defined by the computer program instructions stored in the memory 1410 and/or storage 1412 and controlled by the processor 1404 executing the computer program instructions. An image acquisition device 1420, such as an MR scanning device, Ultrasound device, etc., can be connected to the computer 1402 to input image data to the computer 1402. It is possible to implement the image acquisition device 1420 and the computer 1402 as one device. It is also possible that the image acquisition device 1420 and the computer 1402 communicate wirelessly through a network. The computer 1402 also includes one or more network interfaces 1406 for communicating with other devices via a network. The computer 1402 also includes other input/output devices 1408 that enable user interaction with the computer 1402 (e.g., display, keyboard, mouse, speakers, buttons, etc.). Such input/output devices 1408 may be used in conjunction with a set of computer programs as an annotation tool to annotate volumes received from the image acquisition device 1420. One skilled in the art will recognize that an implementation of an actual computer could contain other components as well, and that FIG. 14 is a high level representation of some of the components of such a computer for illustrative purposes.

[0103] The foregoing Detailed Description is to be understood as being in every respect illustrative and exemplary, but not restrictive, and the scope of the invention disclosed herein is not to be determined from the Detailed Description, but rather from the claims as interpreted according to the full breadth permitted by the patent laws. It is to be understood that the embodiments shown and described herein are only illustrative of the principles of the present invention and that various modifications may be implemented by those skilled in the art without departing from the scope and spirit of the invention. Those skilled in the art could implement various other feature combinations without departing from the scope and spirit of the invention.

1. A method for analyzing an effect of a treatment scenario, comprising:

extracting features for a stenosis of interest from medical image data of a patient;

determining a first fractional flow reserve (FFR) value for the stenosis of interest based on the extracted features using a trained machine-learning based mapping, wherein the trained machine-learning based mapping is trained based on geometric features extracted from synthetically generated stenosis geometries that are not based on patient-specific data;

determining a second FFR value for the stenosis of interest based on one or more modified values of the extracted features using the trained machine-learning

based mapping, the one or more modified values of the extracted features reflecting the treatment scenario; and analyzing the effect of the treatment scenario based on the first FFR and the second FFR.

2. The method of claim 1, further comprising:

receiving a user input modifying one or more values of the extracted features to provide the one or more modified values of the extracted features.

3. The method of claim 1, wherein the trained machine-learning based mapping is trained based on FFR values corresponding to the synthetically generated stenosis geometries computed using computational fluid dynamics (CFD) simulations performed on the synthetically generated stenosis geometries.

4. The method of claim 1, wherein extracting features for a stenosis of interest from medical image data of a patient comprises:

extracting one or more features characterizing a geometry of the stenosis of interest.

5. The method of claim 4, wherein the one or more features characterizing the geometry of the stenosis of interest include one or more of proximal and distal reference diameters, minimal lumen diameter, lesion length, entrance angle, entrance length, exit angle, exit length, percentage of diameter blocked by the stenosis, and percentage of the area blocked by the stenosis.

6. The method of claim 1, wherein extracting features for a stenosis of interest from medical image data of a patient comprises:

extracting one or more features characterizing a morphology of the stenosis of interest.

7. The method of claim 1, wherein extracting features for a stenosis of interest from medical image data of a patient comprises:

extracting one or more features characterizing a geometry of a coronary artery branch in which the stenosis of interest is located.

8. The method of claim 1, wherein extracting features for a stenosis of interest from medical image data of a patient comprises:

extracting one or more features characterizing a geometry of an entire coronary artery tree of the patient.

9. The method of claim 1, wherein extracting features for a stenosis of interest from medical image data of a patient comprises:

extracting one or more features characterizing coronary anatomy and function.

10. An apparatus for analyzing an effect of a treatment scenario, comprising:

a processor; and

a memory storing computer executable instructions, which when executed by the processor cause the processor to perform operations comprising:

extracting features for a stenosis of interest from medical image data of a patient;

determining a first fractional flow reserve (FFR) value for the stenosis of interest based on the extracted features using a trained machine-learning based mapping, wherein the trained machine-learning based mapping is trained based on geometric features extracted from synthetically generated stenosis geometries that are not based on patient-specific data;

determining a second FFR value for the stenosis of interest based on one or more modified values of the